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NEURAL NETWORKS FOR THE CALCULATION OF BANDWIDTH OF RECTANGULAR MICROSTRIP ANTENNAS

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ABSTRACT: Neural models for calculating the bandwidth of electrically thin and thick rectangular microstrip antennas, based on the multilayered perceptrons and the radial basis function networks, are presented. Thirteen learning algorithms, the conjugate gradient of Fletcher-Reeves, Levenberg-Marquardt, scaled conjugate gradient, resilient backpropagation, conjugate gradient of Powell-Beale, conjugate gradient of Polak-Ribière, bayesian regularization, one-step secant, backpropagation with adaptive learning rate, Broyden-Fletcher-Goldfarb-Shanno, backpropagation with momentum, directed random search and genetic algorithm, are used to train the multilayered perceptrons. The radial basis function network is trained by the extended delta-bar-delta algorithm. The bandwidth results obtained by using neural models are in very good agreement with the experimental results available in the literature. When the performances of neural models are compared with each other, the best results for training and test were obtained from the multilayered perceptrons trained by the conjugate gradient of Powell-Beale and Broyden-Fletcher-Goldfarb-Shanno algorithms, respectively.

1. INTRODUCTION

Microstrip antennas (MSAs) have become the favorite choice of antenna designers because they offer the attractive features of low profile, light weight, low cost, conformability to curved surfaces, ease of manufacture, and compatibility with integrated circuit technology [1-18]. A number of methods [1-36] using different levels of approximation have been proposed and used to compute the bandwidth of rectangular MSA, as this is one of the most popular and convenient shapes. These methods can generally be divided into two groups: simple analytical methods and rigorous numerical methods. Simple analytical methods can give a good intuitive explanation of antenna radiation properties. However, these methods do not consider rigorously the effects of surface waves. Exact mathematical formulations in rigorous methods involve extensive numerical procedures, resulting in round-off errors, and may also need final experimental adjustments to the theoretical results. These methods also require

high performance large-scale computer resources and a very large number of computations. Furthermore, most of the previous theoretical and experimental work has been carried out only with electrically thin MSAs, normally of the order of $h/\lambda_d \leq 0.02$, where h is the thickness of the dielectric substrate and λ_d is the wavelength in the substrate. Recent interest has developed in radiators etched on electrically thick substrates. The need for theoretical and experimental studies of MSAs with electrically-thick substrates is motivated by several major factors. Among these is the fact that MSAs are currently being considered for use in millimetre-wave systems. The substrates proposed for such applications often have high relative dielectric constants and, hence, appear electrically thick. The need for greater bandwidth is another reason for studying thick substrate MSAs. Consequently, this problem, particularly the bandwidth aspect, has received considerable attention.

In this paper, models based on artificial neural networks (ANNs) are presented for the bandwidth of both electrically thin and thick rectangular MSAs. Ability and adaptability to learn, generalizability, smaller information requirement, fast real-time operation, and ease of implementation features have made ANNs popular in the last few years [37-40]. Because of these fascinating features, artificial neural networks in this article are used to model the relationship between the parameters of MSA and the measured bandwidth results.

In previous works [35,41-48], we also successfully introduced ANNs to compute the various parameters of the triangular, rectangular and circular MSAs. In reference [35], the bandwidth of rectangular MSAs has been computed by using ANNs. In [35], only the multilayered perceptrons (MLPs) were used as the neural network architecture. However, in this paper, both the MLPs and the radial basis function networks (RBFNs) are used for calculating the bandwidth. Furthermore, in [35], the four learning algorithms, the backpropagation (BP) [49], the delta-bar-delta (DBD) [50], the quick propagation (QP) [51], and the extended delta-bar-delta (EDBD) [52], are used to train the MLPs. However, in this paper, thirteen

learning algorithms, conjugate gradient of Fletcher-Reeves (CGFR) [53], Levenberg-Marquardt (LM) [54,55], scaled conjugate gradient (SCG) [56], resilient backpropagation (RP) [57], Broyden-Fletcher-Goldfarb-Shanno (BFGS) [58], conjugate gradient of Powell-Beale (CGPB) [59,60], conjugate gradient of Polak-Ribière (CGPR) [61], bayesian regularization (BR) [62], one-step secant (OSS) [63], backpropagation with adaptive learning rate (BPALR) [61], backpropagation with momentum (BPM) [61], directed random search (DRS) [64] and genetic algorithm (GA) [65,66] are used to train the MLPs. The radial basis function network is trained by extended delta-bar-delta (EDBD) algorithm. The main aims of this paper are

- to calculate the bandwidth of electrically thin and thick rectangular MSAs by using the MLPs and RBFNs architectures;
- to train the MLPs by the CGFR, LM, SCG, RP, BFGS, CGPB, CGPR, BR, OSS, BPALR, BPM, DRS, and GA, and to train the RBFNs by the EDBD algorithm;
- to compare the bandwidth results of neural models presented in this paper with the results of the conventional methods available in the literature;
- to compare also the bandwidth results of neural models presented in this paper with the results of fuzzy inference systems [36] trained by the improved tabu search algorithm (ITSA) [67], the modified tabu search algorithm (MTSA) [68] and the classical tabu search algorithm (CTSA) [69,70], and with the results of the neural models [35] trained by the BP, DBD, QP, and EDBD algorithms;
- to determine the most appropriate neural model in calculating the bandwidth of rectangular MSAs; and
- to show the superiority of artificial intelligence techniques such as neural networks and fuzzy inference systems over the conventional methods.

In the following sections, the bandwidth of the MSAs, the ANNs, the MLPs and the RBFNs are described briefly, and the application of neural networks to the calculation of the bandwidth of a MSA is then explained.

2. BANDWIDTH OF A RECTANGULAR MICROSTRIP ANTENNA

Figure 1 illustrates a rectangular patch of width W and length L over a ground plane with a substrate of thickness h and a relative dielectric constant ϵ_r . The bandwidth of this antenna can be written as [1]

$$BW = \frac{s-1}{Q_T \sqrt{s}} \quad (1)$$

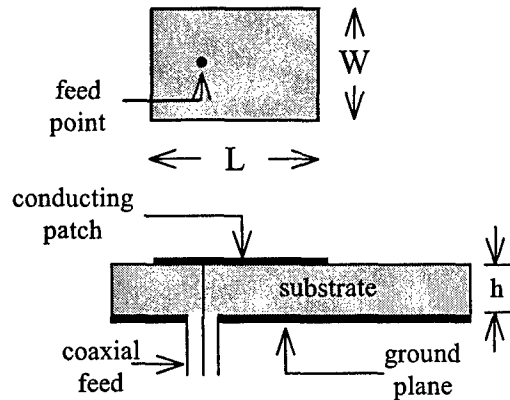


Figure 1. Geometry of rectangular microstrip antenna.

where s is voltage standing wave ratio (VSWR), and Q_T is the total quality factor. The total quality factor, Q_T , can be written as

$$\frac{1}{Q_T} = \left[\frac{1}{Q_r} + \frac{1}{Q_c} + \frac{1}{Q_d} + \frac{1}{Q_s} \right] \quad (2)$$

where the four terms represent the radiation quality factor, the quality factors due to conductor loss, dielectric loss, and surface wave.

Bandwidth was defined by Pozar [23] as the half-power width of the equivalent circuit impedance response. For a series-type resonance, this bandwidth is

$$BW = \frac{2R}{W_r \left. \frac{dX}{dw} \right|_{w_r}} \quad (3)$$

where $Z=R+jX$ is the input impedance at the radian resonant frequency w_r . For a parallel-type resonance, (3) is used with R replaced by G and X replaced by B , where $Y=G+jB$ is the input admittance at resonance. The derivative in (3) can be evaluated by calculating the input impedance at two frequencies near resonance and using a finite difference approximation. The resonant resistance, R , is given by

$$R = R_r + R_d + R_c + R_s \quad (4)$$

where the four terms represent the radiation resistance, the equivalent resistance of the dielectric loss, the equivalent resistance of the conductor loss, and surface wave radiation resistance. The certain way of calculating the total quality factor and the resonant resistance of both electrically thin and thick

rectangular microstrip patch antennas involves the complicated Green function methods and integral transformation techniques. These methods and techniques suffer from a lack of computational efficiency, which in practice can restrict their usefulness because of high computational time and costs.

In this work, a new technique based on the ANNs for solving this problem efficiently is presented. First, the antenna parameters related to the bandwidth are determined, then the bandwidth depending on these parameters is calculated by using the ANNs.

The feeding method or position is not considered in calculating the bandwidth because the feeding method or position does not effect the intrinsic patch bandwidth. The bandwidth of a patch is significantly greater than that of a printed dipole, at least over the range for which the patch actually resonates ($h < 0.12\lambda_0$, where λ_0 is the free space wavelength at the resonant frequency f_r). This fact is consistent with the antenna gain/bandwidth relation to antenna size. Therefore, the effect of the patch width W on the bandwidth of rectangular microstrip antennas must be taken into consideration in the bandwidth calculation of these antennas. From the results of the methods available in the literature [1-36] we see that for a given frequency, larger bandwidth is possible by choosing a thicker substrate and a wider patch. The results also indicate that a lower value of ϵ_r results in a larger bandwidth.

It is clear from the methods and formulas presented by [1-36] that only three parameters, h/λ_0 , W , and the dielectric loss tangent $\tan\delta$, are needed to describe the bandwidth. The wavelength in the dielectric substrate, λ_d , is given as

$$\lambda_d = \frac{\lambda_0}{\sqrt{\epsilon_r}} = \frac{c}{f_r \sqrt{\epsilon_r}} \quad (5)$$

where c is the velocity of electromagnetic waves in free space.

3. ARTIFICIAL NEURAL NETWORKS (ANNs)

ANNs are biologically inspired computer programs designed to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience, not from programming. An ANN is formed from hundreds of single units, artificial neurons or processing elements connected with weights, which constitute the neural structure and are organised in layers. The power of neural computations comes from weight connection in a network. Each neuron has weighted inputs, summation function, transfer

function and one output. The behaviour of a neural network is determined by the transfer functions of its neurons, by the learning rule, and by the architecture itself. The weights are the adjustable parameters and, in that sense, a neural network is a parameterised system. The weighted sum of the inputs constitutes the activation of the neuron. The activation signal is passed through a transfer function to produce the output of a neuron. Transfer function introduces non-linearity to the network. During training, the inter-unit connections are optimised until the error in predictions is minimised and the network reaches the specified level of accuracy. Once the network is trained, new unseen input information is entered to the network to calculate the output for test. ANN represents a promising modelling technique, especially for data sets having non-linear relationships that are frequently encountered in engineering. In terms of model specification, artificial neural networks require no knowledge of the data source but, since they often contain many weights that must be estimated, they require large training sets. In addition, ANNs can combine and incorporate both literature-based and experimental data to solve problems.

There are many types of neural networks for various applications available in the literature [37-40,71]. RBFNs and MLPs are examples of feed-forward networks and both universal approximators. In spite of being different networks in several important respects, these two neural network architectures are capable of accurately mimicking each other [40].

3.1. Multilayered Perceptrons (MLPs)

Multilayered perceptrons (MLPs) [40,49] are the simplest and therefore most commonly used neural network architectures. They have been adapted for the calculation of the bandwidth of the MSA. MLPs can be trained using many different learning algorithms [37-40,71]. In this paper, MLPs are trained with the CGFR, LM, SCG, RP, BFGS, CGPB, CGPR, BR, OSS, BPALR, BPM, DRS, and GA. As shown in Figure 2, an MLP consists of three layers: an input layer, an output layer and an intermediate or hidden layer. Neurons (indicated in Figure 2 with the circle) in the input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum, viz.,

$$y_j = f(\sum w_{ji} x_i) \quad (6)$$

f can be a simple threshold function, a sigmoidal or

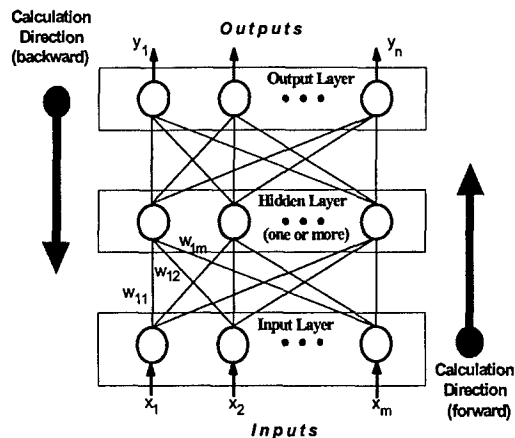


Figure 2. General form of multilayered perceptrons.

hyperbolic tangent function. The output of neurons in the output layer is computed similarly.

Training a network consists of adjusting weights of the network using the different learning algorithms. A learning algorithm gives the change $\Delta w_{ji}(k)$ in the weight of a connection between neurons i and j at time k . The weights are then updated according to the following formula

$$w_{ji}(k+1) = w_{ji}(k) + \Delta w_{ji}(k+1) \quad (7)$$

3.2. Radial Basis Function Networks (RBFNs)

An alternative network architecture to the MLP is the RBFN [72-74]. A network with an internal representation of hidden neurons, radially symmetric, is named as a RBFN. The topology of the RBFN is obviously similar to that of the three-layered MLP, and the differences lie in the characteristics of the hidden neurons. The structure of a RBFN is shown in Figure 3.

The construction of a RBFN in its most basic form involves three entirely different layers. The input layer is made up of source neurons. The second layer is a hidden layer of high dimension serving a different purpose from that in a MLP. This layer consists of an array of neurons. Each neuron contains a parameter vector called a centre. The neuron calculates the Euclidean distance between the centre and the network input vector, and passes the result through a non-linear function. The output layer is essentially a set of linear combiners and supplies the response of the network. The transformation from input layer to the hidden layer is non-linear, whereas the transformation from the hidden layer to the output layer is linear.

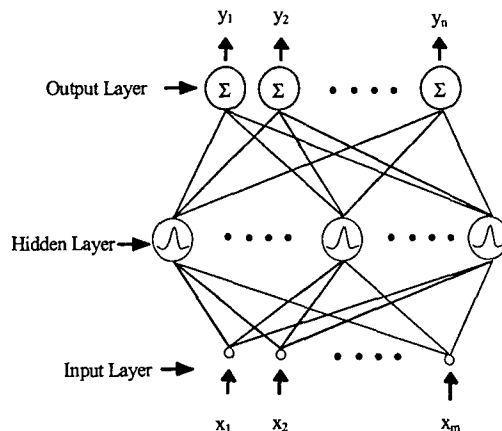


Figure 3. Radial basis function network.

The output of an hidden layer is a function of the distance between the input vector and the stored centre and calculated as

$$O_k = \|X - C_k\| = \sqrt{\sum_{i=1}^N (X_i - C_{ki})^2} \quad (8)$$

The learning consists of using a clustering algorithm for determining the cluster centres (C_k) and a nearest neighbour heuristic for determining the cluster centres. Linear regression, or a gradient descent algorithm is used to determine the weights from the hidden layer to the output layer. In this work, EDBD algorithm is used to train the weights of the layer.

4. NEURAL NETWORKS FOR BANDWIDTH COMPUTATION

ANNs have been adapted for the calculation of the bandwidth (BW) of electrically thin and thick rectangular microstrip antennas. MLPs are trained with the use of CGFR, LM, SCG, RP, BFGS, CGPB, CGPR, BR, OSS, BPALR, BPM, DRS, and GA algorithms. RBFN is trained by using EDBD algorithm. For the neural models, the inputs are h/λ_d , W , and $\tan\delta$, and the output is the measured bandwidth BW_{ME} . A neural model used in calculating the BW is shown in Figure 4.

For the MLPs trained by DRS and GA, input layer has the linear transfer function, the hidden and output layers have the sigmoid function. For the MLPs trained by the other learning algorithms, the input and output layers have the linear transfer function and the hidden layers have the tangent hyperbolic function. In the RBFNs, the sigmoid function was used for the output layer. Training an ANN with the use of a learning algorithm to compute the bandwidth

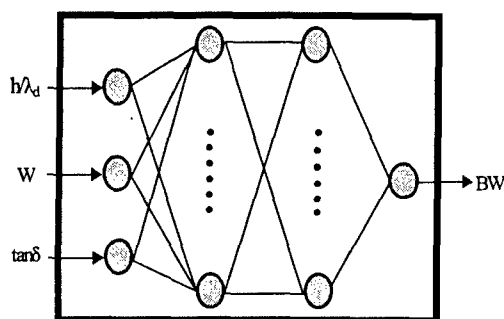


Figure 4. Neural model for bandwidth computation.

involves presenting it sequentially with different sets (h/λ_d , W , $\tan\delta$) and corresponding measured values BW_{ME} . Differences between the target output BW_{ME} and the actual output of the ANNs are evaluated by a learning algorithm. The adaptation is carried out after the presentation of each set (h/λ_d , W , $\tan\delta$) until the calculation accuracy of the network is deemed satisfactory according to some criterion (for example, when the error between BW_{ME} and the actual output for all the training set falls below a given threshold) or the maximum allowable number of epochs or generations is reached.

The training and test data sets used in this paper have been obtained from the previous experimental works [33,34], and are given in Table 1. The 27 data sets in Table 1 were used to train the networks. 6 test data sets which are marked with an asterisk in Table 1 were used for test. The number of neurons in the hidden layers and train epochs for neural models presented here are given in Table 2. 10x7x8 in Table 2 means that the number of neurons was 10, 7, and 8 for the first, second, and third hidden layers, respectively. Initial weights of the neural models were set up randomly.

5. RESULTS AND CONCLUSIONS

The bandwidths calculated by using neural models presented in this paper for electrically thin and thick rectangular microstrip patch antennas are listed in Table 3. For comparison, the results obtained by using the conventional methods [1,21,31-33], and the neural models presented by [35] and the fuzzy inference systems [36] are given in Table 4. EDBD, DBD, BP, QP, ITSA, CTSA, and MTSA in Table 4 represent, respectively, the bandwidths calculated by the neural models [35] trained by EDBD, DBD, BP, QP, and calculated by the fuzzy inference systems [36] trained by ITSA, CTSA, and MTSA. The total absolute errors between the computed and experimental results for neural models, fuzzy inference systems, and conventional methods are listed in Table 5 and Table 6.

Table 1. Measured bandwidth results and dimensions for electrically thin and thick rectangular microstrip antennas.

Patch No	h (mm)	f_r (GHz)	h/λ_d	W (mm)	$\tan\delta$	Measured [33,34] BW_{ME} (%)
1	0.17	7.740	0.0065	8.50	0.001	1.07
2	0.79	3.970	0.0155	20.00	0.001	2.20
3	0.79	7.730	0.0326	10.63	0.001	3.85
4	0.79	3.545	0.0149	20.74	0.002	1.95
5	1.27	4.600	0.0622	9.10	0.001	2.05
6	1.57	5.060	0.0404	17.20	0.001	5.10
7	1.57	4.805	0.0384	18.10	0.001	4.90*
8	1.63	6.560	0.0569	12.70	0.002	6.80
9	1.63	5.600	0.0486	15.00	0.002	5.70
10	2.00	6.200	0.0660	13.37	0.002	7.70*
11	2.42	7.050	0.0908	11.20	0.002	10.90
12	2.52	5.800	0.0778	14.03	0.002	9.30
13	3.00	5.270	0.0833	15.30	0.002	10.00
14	3.00	7.990	0.1263	9.05	0.002	16.00*
15	3.00	6.570	0.1039	11.70	0.002	13.60
16	4.76	5.100	0.1292	13.75	0.002	15.90
17	3.30	8.000	0.1405	7.76	0.002	17.50
18	4.00	7.134	0.1519	7.90	0.002	18.20*
19	4.50	6.070	0.1454	9.87	0.002	17.90
20	4.76	5.820	0.1475	10.00	0.002	18.00
21	4.76	6.380	0.1617	8.14	0.002	19.00
22	5.50	5.990	0.1754	7.90	0.002	20.00
23	6.26	4.660	0.1553	12.00	0.002	18.70
24	8.45	4.600	0.2091	7.83	0.002	20.90
25	9.52	3.580	0.1814	12.56	0.002	20.00
26	9.52	3.980	0.2017	9.74	0.002	20.60
27	9.52	3.900	0.1976	10.20	0.002	20.30*
28	10.00	3.980	0.2119	8.83	0.002	20.90
29	11.00	3.900	0.2284	7.77	0.002	21.96
30	12.00	3.470	0.2216	9.20	0.002	21.50
31	12.81	3.200	0.2182	10.30	0.002	21.60
32	12.81	2.980	0.2032	12.65	0.002	20.40
33	12.81	3.150	0.2148	10.80	0.002	21.20*

*Test data sets

When the performances of neural models presented in this paper and in [35] are compared with each other, the best results for training and test were obtained from the MLP network trained by the CGPB and BFGS, respectively, as shown in Table 5. However, among the neural models, the highest accuracy in the total absolute errors was achieved with the CGFR algorithm. When the two heuristic approaches were compared with each other, the results of DRS were found better than those of the GA. It is also clear from Table 5 that in most cases the results of neural models presented in this paper are better than those of the neural models presented by [35] and that the best result in the total absolute errors is obtained from the fuzzy inference systems trained by ITSA. However, the train absolute error of the fuzzy inference systems trained by ITSA is larger than that of the MLPs trained by CGFR, LM, SCG, CGPB, and CGPR algorithms.

Table 2. The ANN configurations and the number of train epochs for neural models presented in this paper.

ANN Architectures/ Algorithms		The number of neurons in the hidden layers	The number of train epochs
MLPs	CGFR	10 x 7 x 8	2 500
	LM	6 x 3	201
	SCG	11 x 8 x 7	1 200
	RP	12 x 10	6 500
	BFGS	10 x 5	700
	CGPB	7 x 7 x 4	1 500
	CGPR	7 x 7 x 4	1 500
	BR	3 x 4 x 3	290
	OSS	10 x 8 x 8	2 500
	BPALR	45 x 35 x 35	2 500
	BPM	45 x 35 x 35	5 000
	DRS	12 x 6	740
	GA	20 x 25	1 850
RBFN	EDBD	20 x 6	185 200

It can be clearly seen from Tables 4 and 6 that the conventional methods give comparable results-some cases are in very good agreement with measurements, and others are far off. When the results of neural models and fuzzy inference systems are compared with the results of the conventional methods, the results of all neural models and fuzzy inference systems are better than those predicted by the conventional methods. The very good agreement between the measured bandwidth values and the computed bandwidth values of neural models and fuzzy inference systems supports the validity of the artificial intelligence techniques and also illustrates the superiority of artificial intelligence techniques over the conventional methods.

A distinct advantage of neural computation is that, after proper training, a neural network completely bypasses the repeated use of complex iterative processes for new cases presented to it. For engineering applications, the simple models are very usable. Thus the neural models given in this work can also be used for many engineering applications and purposes.

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Table 3. Comparison of measured and calculated bandwidths obtained by using neural models presented in this paper for electrically thin and thick rectangular microstrip antennas.

Patch No	Measured BW _{ME} (%) [33,34]	Present Neural Models													
		MLP													RBFN
		CGFR	LM	SCG	RP	BFGS	CGPB	CGPR	BR	OSS	BPALR	BPM	DRS	GA	EDBD
1	1.070	1.069	1.071	1.071	1.070	1.070	1.070	1.070	1.070	1.067	1.071	1.068	1.400	1.573	1.048
2	2.200	2.199	2.200	2.200	2.201	2.202	2.200	2.200	2.200	2.203	2.200	2.201	2.182	2.620	2.292
3	3.850	3.850	3.850	3.850	3.850	3.850	3.851	3.850	3.850	3.853	3.837	3.840	3.336	3.288	3.840
4	1.950	1.949	1.950	1.949	1.950	1.952	1.950	1.950	1.950	1.948	1.945	1.949	1.951	1.943	1.899
5	2.050	2.050	2.050	2.050	2.051	2.048	2.050	2.050	2.050	2.049	2.061	2.062	2.210	2.120	2.077
6	5.100	5.101	5.100	5.100	5.099	5.100	5.099	5.100	5.100	5.100	5.097	5.100	5.223	4.816	5.024
7	4.900*	4.560	4.900	4.766	4.922	4.764	4.016	4.011	5.175	4.137	4.233	4.300	4.571	4.506	4.437
8	6.800	6.800	6.800	6.800	6.800	6.798	6.801	6.800	6.799	6.811	6.790	6.801	6.754	7.076	6.744
9	5.700	5.699	5.700	5.700	5.700	5.700	5.702	5.700	5.701	5.702	5.694	5.701	5.632	5.470	5.806
10	7.700*	7.811	7.763	7.862	8.132	7.639	7.719	7.691	7.869	7.760	7.705	7.536	7.891	8.061	7.968
11	10.900	10.899	10.901	10.903	10.900	10.926	10.900	10.900	10.900	10.910	10.902	10.906	11.285	11.250	11.080
12	9.300	9.299	9.299	9.305	9.299	9.301	9.300	9.301	9.302	9.271	9.301	9.298	9.425	9.451	9.471
13	10.000	10.001	10.001	9.999	10.001	9.999	9.999	9.999	9.998	10.016	9.980	9.997	9.983	9.864	9.813
14	16.000*	15.954	15.918	16.161	15.995	15.890	16.063	16.100	16.337	16.396	15.982	16.182	15.924	16.167	15.940
15	13.600	13.601	13.599	13.595	13.605	13.548	13.598	13.600	13.600	13.598	13.576	13.593	13.169	13.135	13.225
16	15.900	15.899	15.901	15.899	15.902	15.919	15.902	15.901	15.905	15.900	15.905	15.906	16.003	16.086	16.106
17	17.500	17.499	17.504	17.496	17.493	17.496	17.499	17.502	17.501	17.482	17.494	17.499	17.284	17.516	17.417
18	18.200*	18.345	18.422	18.217	18.179	18.365	18.297	18.300	18.311	18.395	18.458	18.537	18.340	18.394	18.381
19	17.900	17.877	17.847	17.853	17.824	17.850	17.871	17.869	17.860	17.864	17.861	17.890	17.947	17.883	17.996
20	18.000	18.023	18.055	18.048	18.066	18.051	18.035	18.034	18.019	18.049	18.036	18.010	18.129	18.046	18.170
21	19.000	19.004	19.004	19.013	19.026	19.016	18.999	18.999	19.037	19.055	19.098	19.146	19.103	19.050	19.035
22	20.000	20.000	19.991	19.998	19.991	19.989	20.000	20.000	19.974	19.919	19.801	19.764	19.893	19.801	19.733
23	18.700	18.699	18.696	18.695	18.696	18.797	18.698	18.697	18.699	18.690	18.709	18.719	18.572	18.419	18.655
24	20.900	20.919	20.897	20.897	20.893	20.887	20.903	20.906	20.888	20.927	21.009	21.016	21.135	21.136	21.076
25	20.000	20.000	20.000	20.005	20.000	19.819	20.002	20.000	19.989	19.999	19.902	19.902	19.859	19.807	19.792
26	20.600	20.600	20.592	20.606	20.579	20.610	20.596	20.604	20.667	20.612	20.596	20.593	20.969	20.917	20.797
27	20.300*	20.237	20.455	20.562	20.429	20.484	20.505	20.517	20.604	20.512	20.397	20.382	20.818	20.796	20.638
28	20.900	20.873	20.910	20.889	20.921	20.913	20.891	20.883	20.841	20.958	21.046	21.033	21.247	21.190	21.175
29	21.960	21.948	21.953	21.963	21.934	21.941	21.952	21.955	21.941	21.939	21.818	21.861	21.521	21.702	21.782
30	21.500	21.545	21.520	21.506	21.573	21.583	21.522	21.523	21.571	21.503	21.552	21.526	21.439	21.435	21.513
31	21.600	21.571	21.590	21.596	21.541	21.525	21.591	21.589	21.566	21.557	21.422	21.444	21.298	21.385	21.339
32	20.400	20.405	20.401	20.400	20.414	20.494	20.401	20.401	20.402	20.403	20.528	20.520	20.499	20.646	20.479
33	21.200*	21.265	21.493	21.481	21.370	21.270	21.431	21.431	21.279	21.407	21.197	21.218	21.166	21.309	21.180

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Table 4. Bandwidths obtained from the conventional methods and artificial intelligence techniques available in the literature for electrically thin and thick rectangular microstrip antennas.

Patch No	Measured BW _{ME} (%) [33,34]	Conventional Methods in the Literature					Artificial Intelligence Techniques in the Literature						
		[21]	[1]	[31]	[33]	[32]	Neural Models [35]				Fuzzy Inference Systems [36]		
							EDBD	DBD	BP	QP	ITSA	CTSA	MTSA
1	1.070	0.82	0.84	0.30	1.20	0.26	1.081	1.068	1.178	1.271	1.070	1.070	1.070
2	2.200	1.45	2.03	0.87	2.78	0.75	2.193	2.197	2.304	2.117	2.200	2.200	2.200
3	3.850	2.99	3.76	1.88	5.03	1.64	3.840	3.854	3.670	3.753	3.848	3.850	3.850
4	1.950	1.29	1.69	0.72	2.46	0.61	1.948	1.948	1.905	2.034	1.950	1.959	1.950
5	2.050	1.54	1.90	0.72	4.09	0.84	2.046	2.047	2.117	2.612	2.051	2.050	2.050
6	5.100	4.21	5.14	2.67	6.46	2.35	4.945	5.340	5.211	4.837	5.101	5.100	5.100
7	4.900	3.96	4.87	2.51	6.17	2.20	4.916	4.898	4.831	4.854	4.899	4.900	4.895
8	6.800	5.98	6.70	3.69	8.12	3.43	6.824	6.788	6.887	6.757	6.775	6.595	6.798
9	5.700	4.76	5.69	3.02	7.12	2.78	5.679	5.718	5.822	5.783	5.699	5.676	5.711
10	7.700	7.29	7.81	4.41	9.16	4.20	8.006	7.865	7.727	7.730	7.759	7.877	7.769
11	10.900	11.31	10.88	6.39	11.72	6.50	10.858	10.901	11.040	10.998	10.906	11.217	10.896
12	9.300	9.14	9.26	5.36	10.42	5.26	9.336	9.287	9.155	9.085	9.255	9.476	9.287
13	10.000	10.30	10.14	5.88	11.15	5.83	9.990	10.000	10.092	10.131	10.003	9.860	9.994
14	16.000	18.42	15.64	9.41	15.16	10.36	15.975	15.862	15.940	15.851	16.005	15.998	16.139
15	13.600	13.84	12.75	7.53	13.14	7.90	13.607	13.601	13.528	13.388	13.598	13.174	13.600
16	15.900	18.06	15.73	9.35	15.11	10.50	15.881	15.917	15.994	16.100	15.914	16.050	15.905
17	17.500	15.29	18.48	8.39	17.00	11.28	17.523	17.480	17.349	17.264	17.450	17.442	17.324
18	18.200	13.62	20.09	8.15	17.77	12.18	18.254	18.433	18.372	18.339	18.288	18.357	18.284
19	17.900	14.54	19.17	8.31	17.34	11.70	17.844	17.917	17.949	17.947	17.845	17.884	17.797
20	18.000	14.08	19.46	8.19	17.47	11.80	18.016	18.091	18.101	18.129	18.060	18.050	17.977
21	19.000	12.45	21.47	7.95	18.42	12.93	19.113	19.054	19.113	19.094	18.955	18.988	19.110
22	20.000	10.73	23.41	7.63	19.29	14.10	19.818	19.766	19.878	19.883	19.999	19.714	19.955
23	18.700	13.01	20.55	8.10	18.01	12.57	18.804	18.620	18.433	18.599	18.690	18.603	18.688
24	20.900	7.85	28.24	6.76	21.26	16.49	21.009	21.101	21.170	21.163	20.896	21.080	20.917
25	20.000	10.10	24.27	7.46	19.66	14.54	19.851	19.842	19.857	19.836	19.997	19.790	20.035
26	20.600	8.45	27.17	7.02	20.85	16.10	20.608	20.760	20.916	20.900	20.602	20.759	20.478
27	20.300	8.76	26.59	7.10	20.61	15.76	20.524	20.608	20.724	20.734	20.296	20.599	20.274
28	20.900	7.63	28.64	6.67	21.40	16.65	20.977	21.147	21.241	21.231	20.909	21.145	21.056
29	21.960	6.50	31.03	6.14	22.26	17.56	21.885	21.777	21.557	21.609	21.960	21.741	21.973
30	21.500	6.92	30.06	6.32	21.91	17.13	21.495	21.469	21.412	21.433	21.510	21.461	21.580
31	21.600	7.11	29.56	6.41	21.73	16.95	21.535	21.317	21.342	21.249	21.566	21.309	21.377
32	20.400	8.26	27.39	6.90	20.92	16.07	20.500	20.592	20.569	20.498	20.401	20.526	20.514
33	21.200	7.39	29.07	6.54	21.55	16.77	21.460	21.184	21.148	21.103	21.221	21.178	21.173

Table 5. Train, test and total absolute errors between the measured and calculated bandwidths for various neural networks and fuzzy inference systems.

Artificial Intelligence Techniques		Learning Algorithms	Train Absolute Errors (%)	Test Absolute Errors (%)	Total Absolute Errors (%)
Present Neural Models	MLP	CGFR	0.199	0.770	0.969
		LM	0.194	0.815	1.009
		SCG	0.174	1.017	1.191
		RP	0.421	0.779	1.200
		BFGS	0.824	0.726	1.550
		CGPB	0.136	1.499	1.635
		CGPR	0.141	1.546	1.687
		BR	0.410	1.275	1.685
		OSS	0.499	1.833	2.332
		BPALR	1.345	1.048	2.393
		BPM	1.229	1.383	2.612
		DRS	5.044	1.288	6.332
		GA	6.069	1.721	7.790
	RBFN	EDBD	3.633	1.330	4.963
Fuzzy Inference Systems [36]		ITSA	0.384	0.178	0.562
		MTSA	1.270	0.350	1.620
		CTSA	3.435	0.657	4.092
Neural Models in the Literature [35]	MLP	EDBD	1.430	0.885	2.315
		DBD	2.267	0.862	3.129
		BP	4.158	0.804	4.962
		QP	4.921	0.895	5.816

Table 6. The total absolute errors between the measured and calculated bandwidths for the conventional methods in the literature.

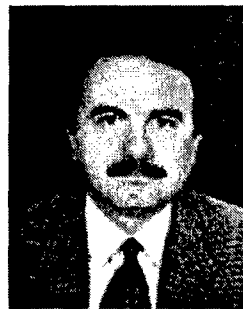
Conventional Methods in the Literature	[21]	[1]	[31]	[33]	[32]
Total absolute deviations from the measured data (%)	178.69	88.76	266.93	23.92	140.02

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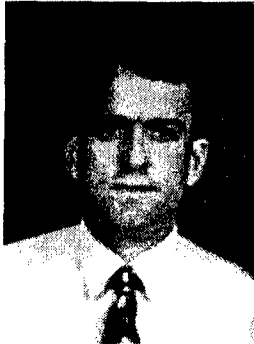


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